SHORT COMMUNICATION

Towards AI-augmented radiology education: a web-based application for perception training in chest X-ray nodule detection

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Objectives: Artificial intelligence (AI)-based applications for augmenting radiological education are underexplored. Prior studies have demonstrated the effectiveness of simulation in radiological perception training. This study aimed to develop and make available a pure web-based application called *Perception Trainer* for perception training in lung nodule detection in chest X-rays.

Methods: Based on open-access data, we trained a deep-learning model for lung segmentation in chest X-rays. Subsequently, an algorithm for artificial lung nodule generation was implemented and combined with the segmentation model to allow on-the-fly procedural insertion of lung nodules in chest X-rays. This functionality was integrated into an existing zero-footprint web-based DICOM viewer, and a dynamic HTML page was created to specify case generation parameters.

Results: The result is an easily accessible platform-agnostic web application available at: https://castlemountain.dk/mulrecon/perceptionTrainer.html.

The application allows the user to specify the characteristics of lung nodules to be inserted into chest X-rays, and it produces automated feedback regarding nodule detection performance. Generated cases can be shared through a uniform resource locator.

Conclusion: We anticipate that the description and availability of our developed solution with open-sourced codes may help facilitate radiological education and stimulate the development of similar AI-augmented educational tools.

Advances in knowledge: A web-based application applying AI-based techniques for radiological perception training was developed. The application demonstrates a novel approach for on-the-fly generation of cases in chest X-ray lung nodule detection employing deep-learning-based segmentation and lung nodule simulation.

INTRODUCTION

Artificial intelligence (AI)-based techniques have great potential for improving radiological workflow. While there has been a poorly informed narrative of "radiologists becoming replaced by AI", one important application of AI is to assist the radiologist in detecting and classifying abnormalities. AI is expected to function as a "co-pilot" in reducing error and the burden of repetitive tasks, and not function as a replacement for radiologists.[1] Thus, image interpretation will, at least for the foreseeable future, rely on human expertise.

In the education of radiologists, the acquisition of expertise is task-specific rather than innate and founded on deliberate practice.[2] It is estimated that 60–80% of radiological errors are attributable to perceptual errors.[2] Recent studies have demonstrated that interactive computer-based perceptual learning can contribute to acquiring expertise in several medical imaging tasks, such as lung nodule detection on chest X-ray (CXR) images.[2–4] Radiology educators have encouraged developing and disseminating easily accessible interactive educational content with elements of gamification.[5] Currently, such

Figure 1. Development overview. (**a**) Chest X-rays with accompanying lung masks were used as training data to develop a U-net-based model for lung segmentation, which was converted to tensorflow.js format. (**b**) A JavaScript-based algorithm for lung nodule simulation was created. (**c**). The tensorflow.js segmentation model and nodule simulation algorithm were coupled with a web-based DICOM viewer (**d**). An interactive web-based application to display feedback and provide input for lung nodule generation to the web-based DICOM viewer was developed.
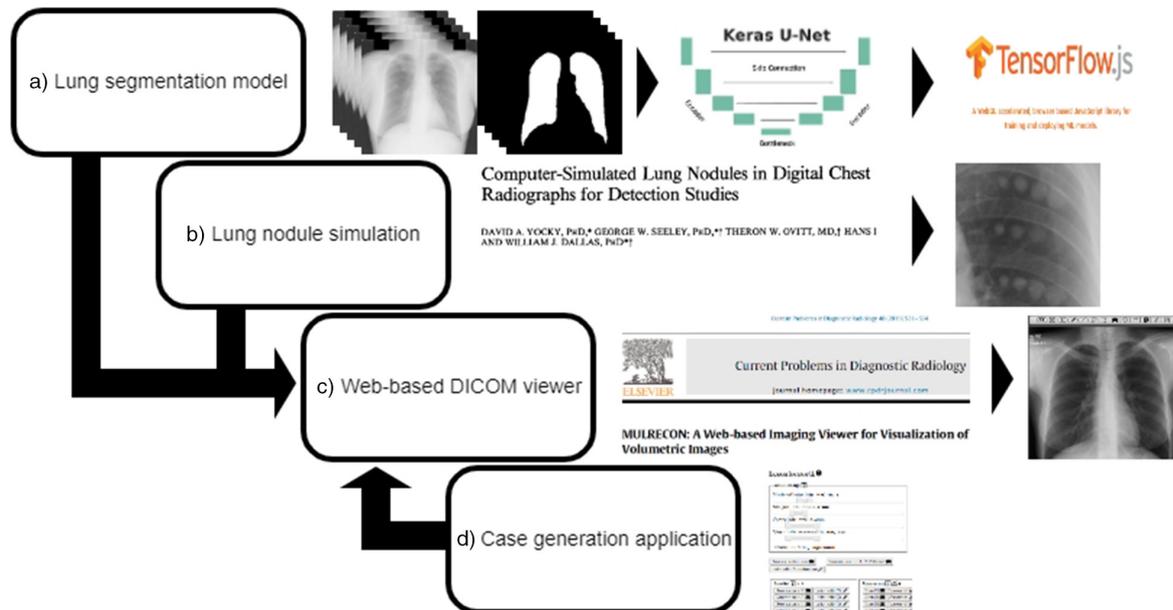
software solutions are relatively scarce with limited reach, which can be explained partly by labor-intensive case curation and focus on desktop-based solutions.[5] The radiological community has emphasized that AI applications for augmenting radiological education are underexplored.[6] Along these lines, Tajmir and colleagues suggest using AI to enhance radiology education by artificially generating clinical cases, which can be achieved by simulating lesions on top of previous imaging studies reducing the need for identifying real clinical cases.[7] Furthermore, web-based applications can provide an interactive solution with on-demand access as desired by contemporary radiology trainees.[8]

Considering these aspects, we have developed and now showcased *Perception Trainer*, a web-based perception training application for lung nodule detection in CXRs. The application utilizes deep learning-based segmentation in combination with computer-simulated lung nodules for automatic case generation. A step-by-step description of how to use the application is provided.

METHODS AND MATERIALS
An overview of the development process is shown in Figure 1.

In brief, a deep learning model for lung segmentation of CXRs was constructed and converted to a web-based format. An algorithm for automatically generating and inserting simulated lung nodules was coupled with a web-based DICOM viewer, where the lung segmentation model enables the insertion of nodules within the lung fields. Finally, a web-based interface was developed to allow the trainee to adjust the parameters for lung nodule simulation. More details are provided in the subsections below.

Data sources
To construct the CXR lung segmentation model, this study used normal CXRs in frontal projection with accompanying ground truth lung masks available in 8-bit grayscale format from three sources[9,10] (Table 1).

Segmentation model for lung segmentation
The model was implemented in Python using the Keras deep learning framework, which runs on top of TensorFlow's machine learning and AI platform (https://www.tensorflow.org/). The U-Net, a convolutional neural network image segmentation architecture, was utilized similarly as described elsewhere.[11] In

Table 1. Data sources used for training the chest X-ray (CXR) lung segmentation model

Data source	Images
Montgomery County CXR set	80 normal CXRs
Shenzhen Hospital CXR set	340 normal CXRs
Japanese Society of Radiological Technology database CXR set	93 normal CXRs and 154 CXRs with a small lung nodule

brief, the 8-bit grayscale input images and accompanying masks (n = 667) were resized to 128 × 128 pixel images. We set aside 100 images as a holdout test set and split the remainder of the data into 85% training and 15% validation. We trained the U-net model using the aforementioned input images and masks with the Adam optimizer and binary cross-entropy loss. All training was performed in the Google Colab environment, Python 3.9.14. (https://www.python.org/). The segmentation model was evaluated regarding the DICE coefficient, a similarity index ranging from 0 to 1 in terms of the overlap between the ground truth segmentation mask and the calculated mask.

Model conversion to a tensorflow.js format

Only recently, it was believed that computation-intensive deep learning models could not effectively run in web browsers. However, several JavaScript-based deep learning frameworks have emerged that harness the acceleration mechanisms offered by current web browsers. Tensorflow.js is one of these new JavaScript libraries and allows deep learning models to run locally in the browser.[12] We converted the above-mentioned Keras-based model to a TensorFlow.js-compatible format.

Web-based DICOM viewer integration

We customized an existing pure web-based DICOM viewer with a high usability score.[13,14] This viewer incorporates typical PACS viewer functionalities and is written in HTML5/Javascript, incorporating jQuery UI (https://jqueryui.com/) for user interface and interaction. The viewer accepts imaging studies in the DICOM format. We utilized the TensorFlow.js model loading application programming interface (API) to integrate the lung segmentation model into the viewer. A JavaScript module containing functions to provide conversion of loaded DICOM-based frontal CXRs to an 8-bit grayscale format compatible with the tensorflow.js model was written. The integrated tensorflow.js model outputs a lung segmentation mask based on the input frontal CXR, allowing subsequent random insertion of simulated lung nodules within the segmented lung fields. In addition, we used the image data transformation functionality of tensorflow.js to provide random transformations of CXRs, *i.e.,* rotation, shearing, and translation. A JavaScript module for the display of a case assessment widget was implemented in the imaging viewer.

Lung nodule simulation

Analogously to the simulation approach Yocky et al described,[15] we implemented a Javascript module for computer generation and insertion of CXR lung nodules. Such simulation technique has been shown to yield nodules radiographically indistinguishable from true lung nodules.[15] In brief, the starting point is a randomly rotated spheroid shape, and to imitate real nodules, different degrees of nodule surface irregularity is introduced based on random Perlin noise loops. Derived from the available lung segmentation, the individual noise properties and the background pixel value of the lungs are incorporated into the simulated nodules to make them look more realistic. Also, different variations and strengths of blur convolutional filters are applied to nodules. Finally, an α blending technique is utilized such that the simulated nodule is pixelwise overlaid on the original data by gradually fading one image into another. Nodules are randomly

inserted within the segmented lung fields. The display signal-to-noise ratio is calculated for each nodule, *i.e.,* the difference in signals (nodule and background area around the nodule) over the total noise. Three radiologists participated in an observer study to verify the realism of the implemented lung nodule simulation method. They rated real and simulated lung nodules using a likelihood score from 1 (absolutely inserted/simulated) to 10 (absolutely real). Please see supplementary File A for more details.

Case generation and assessment application

A dynamic HTML page was created to specify parameters for nodule generation to feed into the case viewer (*i.e.,* range of the number, size, opacity, and margin indistinctiveness of nodules). This information is encoded into a JavaScript Object Notation format as a query string allowing the passing of data to the HTML page of the viewer by simply appending it to the end of the uniform resource locator (URL) in question. Upon instantiation of a case, the above-referenced JavaScript modules for lung segmentation, lung nodule simulation, insertion, and display of the case assessment widget are invoked by the query string. Consequently, a case is created with random placement and characteristics of nodules within the parameters specified.

The HTML Web Storage API was used to store the results of case assessments locally in the web browser allowing subsequent review.

Of note, the placement and generation of simulated nodules are based on seeded random number generation; that is, a generator is initialized with a seed (in our case, the number of milliseconds since January 1, 1970, is encoded in the URL), which ensures that the same sequence of numbers is always output. When a case has been instantiated, it is possible to construct a URL containing the case specifications and seed to feed into the lung nodule simulation algorithm. Subsequently, the case in question with the exact same lung nodules can be procedurally reproduced, omitting the need to save additional extensive image data.

RESULTS

The resulting single-page web application is platform-agnostic, requires no installation, and thus enables ubiquitous access. Figure 2 shows the initial interface available to users after accessing the web application page. It can be used directly by accessing the project website at https://castlemountain.dk/mulrecon/perceptionTrainer.html, where written and video instructions can also be found. In addition, sample case CXRs and the source code are available. Tooltips provide the user with additional information about application features. Chest X-rays in DICOM format for case generation have been placed in the application folder on a web server, referenced in the CSV file. It is also possible to download the application files and upload them to a personal web server, thereby enabling the dissemination of a selection of one's CXR DICOM files.

The user interface is divided into three fields.

- Nodule settings: This field allows the user to specify the characteristics of lung nodules to be inserted into generated

Figure 2. The interface for case generation and review. (**a**) Nodule settings. (**b**) Case list field. (**c**) Case review field. (**d**) Statistics tooltip based on case assessments completed in the local browser. (**e**) Buttons to edit and generate random cases based on the "Case list" as well as a button to create a case based on a locally stored DICOM file.
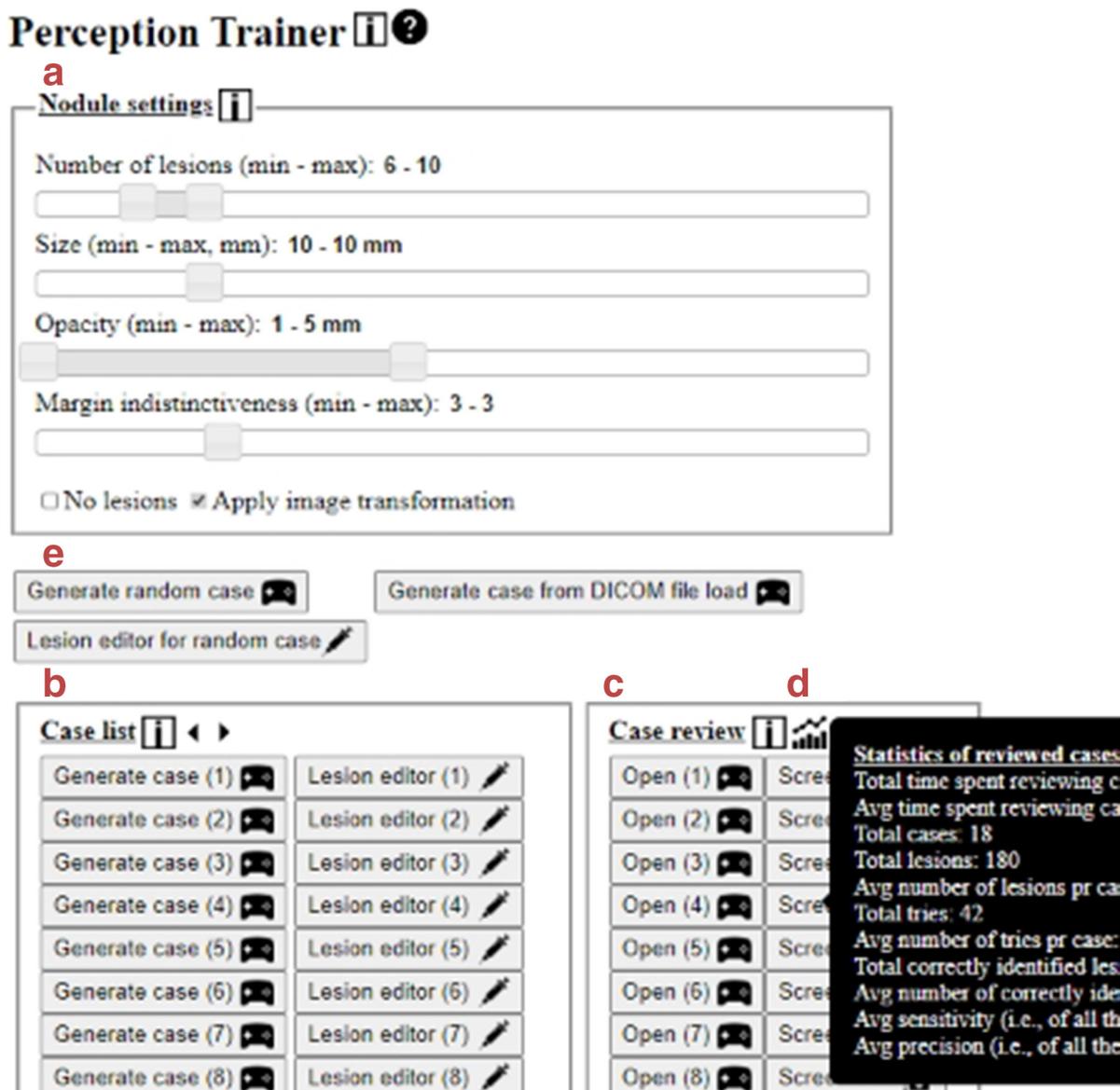
cases via range sliders, *i.e.,* nodule number, size (lower size limit 3 mm per the definition of a pulmonary nodule), opacity, and margin. In addition, checkboxes let the user select "No lesions" and whether to apply random image transformation to generated cases, "Apply image transformation."

- Case list: A list of the available DICOM CXR files as specified in the CSV file with an associated "Generate case" button. Clicking this button will open the imaging viewer with settings for nodule generation, as described above. Another option is to generate a random case from the case list based on the specified lesion settings (*i.e.,* "Generate random case"). Moreover, the "Generate case from DICOM file load" button provides a way to use a locally stored DICOM CXR file for case creation.

Hence, using this last option, no data are sent or kept outside the user's device, guaranteeing the privacy of sensitive data.

- Case review: Tooltip with statistics and an entry for each case assessment completed, including a screenshot and the option to re-review (based on the saved URL containing the unique seed in question for case replication) the case in question (Figure 2).

Case generation, perception training, and feedback

Once a case is instantiated by clicking one of the above-mentioned buttons, the imaging viewer will launch in a new window with the settings URL encoded as previously described. The imaging viewer interface is shown in Figure 3. A top toolbar

Figure 3. Screenshots of the imaging viewer interface before (**a-b**) and after (**c-d**) having clicked "Review placed markers." The "Case assessment widget" has been magnified in (**b,d**). One marker was incorrectly placed (**c**), which is signified with a red cross. One nodule was not identified (**c**) and was highlighted by a yellow circle through the on mouse over function in the "List of synthetic lesions."
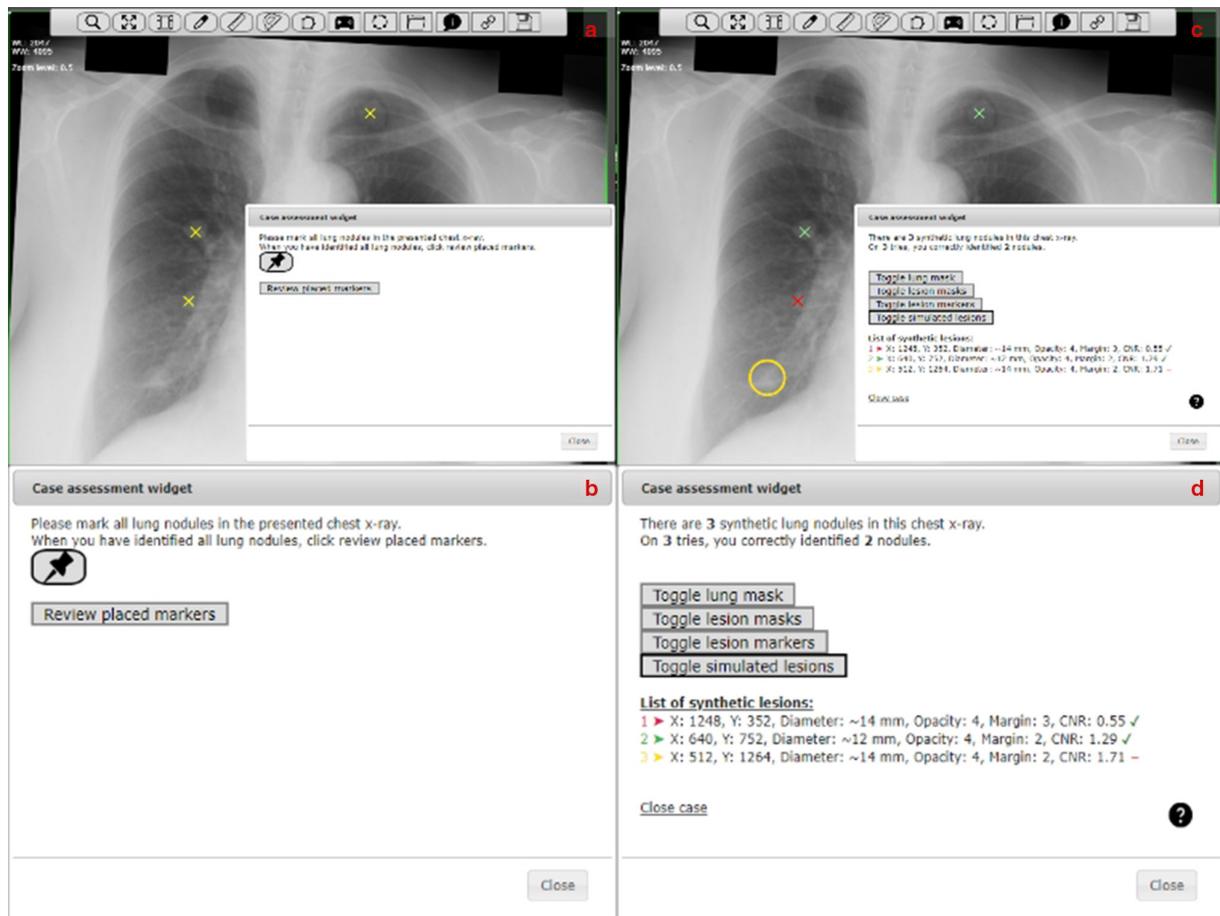
provides DICOM viewer functionality adopted for the evaluation of CXRs. To the left, the CXR at hand is displayed. To the right, a dialog widget is shown by default. This widget prompts the user to mark the lung nodules in the presented CXR.

Subsequently, feedback is elicited consisting of the following elements: (A) color-coded feedback markers for correct (green) and incorrectly placed markers (red), (B) a list of the simulated lung nodules displaying their characteristics and associated contrast-to-noise ratio. On mouse, over functionality will highlight the nodule in question.

Moreover, four buttons provide options to toggle the lung mask, nodule masks, markers, and simulated lung nodules (Figure 3)

Manual case generation and sharing
A *Lesion editor* widget is also available. The editor facilitates the insertion of nodules at specific sites in the CXR (Figure 4).

The *Get URL* toolbar button provides the means to add written case information and retrieve the resulting URL containing the seed needed for case replication, which makes it easy to share a specific case via the Internet (Figure 4). Note: This option is

unavailable when generating a case based on a locally stored CXR DICOM file.

### Tensorflow segmentation model and lung nodule simulation method
Regarding metrics, the developed tensorflow.js model for lung segmentation has a size of 5.2 megabytes and yielded a mean ($\pm$SD) dice coefficient of 94.3 ($\pm$5.6)%. The observer study did not reveal a significant difference in the ability of any radiologist to discriminate between real and simulated lung nodules (Supplementary File A).

DISCUSSION
This paper showcases an AI-augmented web-based application for perception training in CXR nodule detection. Auffermann and colleagues have previously demonstrated that lung nodule identification can be improved using a desktop-based software designed for conducting diagnostic accuracy studies with manually inserted simulated lesions.[3]

Our application is an extension of the methodology employed by Auffermann et al. to the best of our knowledge, combining a deep-learning-based technique with lesion simulation for

Figure 4. Screenshot of the imaging viewer interface in editor mode. The blue box shows the lesion editor widget magnified where lesion #6 has been highlighted (purple circle) on the chest X-ray using the on mouse over function. Clicking on the "syringe" button allows the insertion of a nodule with the specified settings by clicking on the chest X-ray at the desired location. The red box shows the Get URL widget where a URL can be obtained (*i.e.,* "Copy URL to clipboard"), which allows sharing of a created case.
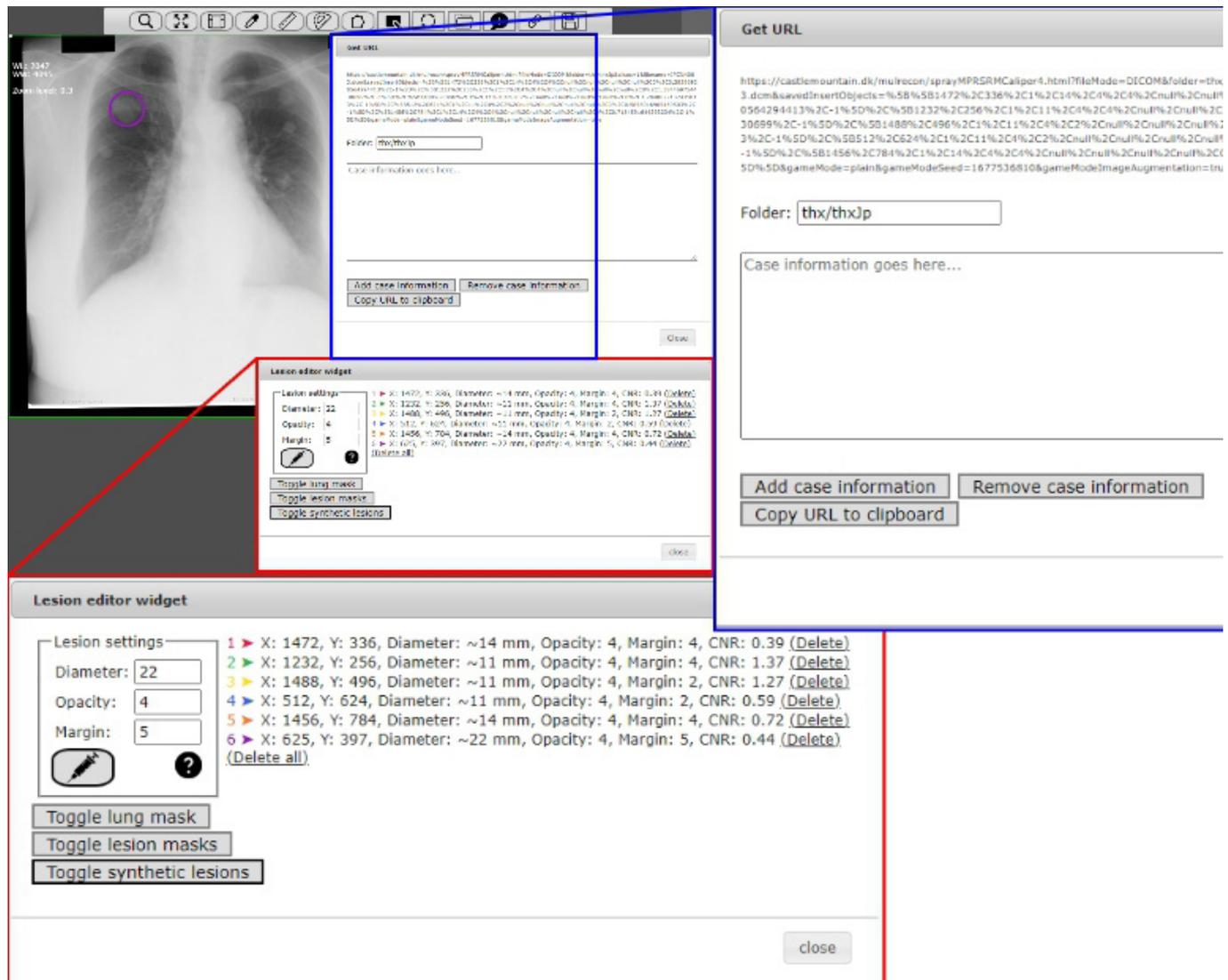
automatic on-the-fly case generation in a web-based format has yet to be described.

While our presented application facilitates the acquisition of *implicit* perceptual skills, trainees need to obtain *explicit* knowledge of pathology and imaging techniques. Hence, the application can be a helpful adjunct in radiology education, providing an easily accessible option for high-volume and intensity training of perceptual skills. Consequently, it can alleviate some of the feedback tasks normally provided by attending faculty members, freeing resources to focus on teaching the finer points of image interpretation.

A web-based format offers well-recognized advantages in terms of application accessibility and scalability and could indeed be helpful in blended learning regimes. Nevertheless, because

we wanted to make the application available for upload and execution on a personal web server, we did not provide database integration in this initial iteration, which would allow the saving of user statistics for benchmarking and longitudinal progress tracking. However, such an extension incorporating more educational feedback elements is a future developmental option to explore.

Due to the modular implementation and the employed imaging viewer primarily built for volumetric datasets, adaptation to CT is another avenue for further development (*e.g.,* liver/lung segmentation and insertion of simulated liver metastases/lung lesions).

In conclusion, we developed an open-access AI-augmented web-based application for perception training in CXR lung nodule

detection. Our vision of this work is that the description and availability of our solution may help facilitate radiology education and future implementations of AI-augmented educational tools.

AUTHOR CONTRIBUTORS

All authors attest that they meet the current International Committee of Medical Journal Editors (ICMJE) criteria for Authorship.Conceptualization: All authors; Data curation: All authors; Formal analysis: All authors; Investigation: All authors; Methodology: All authors; Software: JB; Supervision: All authors; Validation: IS, JT, JBF; Visualization: All authors; Writing - original draft: JB; Writing - review & editing: All authors.

DECLARATIONS OF INTEREST

The authors declare that they have no conflict of interest, have full control of all primary data, and agree to allow the journal to review their data if requested.

HUMAN RIGHTS

The authors declare that the work described has been carried out in accordance with the Declaration of Helsinki of the World Medical Association, revised in 2013 for experiments involving humans.

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